Application area 2: AI and Travel Demand Modeling

This section, which focuses on AI applications for modeling the demand side of transportation systems, includes two contributions. The first contribution, by Avineri, first presents the grounds that justify the application of AI techniques to travel behavior modeling. The article then discusses the applications of a wide range of AI paradigms to travel behavior research including fuzzy set theory, neural networks, genetic algorithms, and multi-agent simulations. The second contribution, by Reinke, discusses some additional opportunities for AI in urban travel demand forecasting.

Travel Behavior Research

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WHAT MAKES AI RELEVANT AND APPROPRIATE FOR THE ANALYSIS AND MODELING OF TRAVEL BEHAVIOR?

Travel behavior has been an area of great interest to practitioners, researchers and policy makers interested in the demand side of transport systems. The travel choices made by travelers have a direct impact on the performance of transport systems and networks. Moreover, our travel behavior generates both positive and negative effects on our wealth, health and well-being. In addition, travel behavior arising from the choices of individuals is perhaps the most significant determinant of effectiveness of transport policies and schemes. It is therefore desirable to understand and predict how people make travel choices, how travel choices might affect the overall performance of the transport system, and how travelers' behavior can be influenced in order to make it more efficient, safe and sustainable.

In the conventional modeling approach applied in transportation planning the model has generally been subdivided into four stages: trip generation, trip distribution, mode choice, and traffic assignment. Travel choice models applied in these four stages are designed to emulate the behavior of travelers over time and space and to predict changes in system performance, when influencing conditions are changed. Commonly it is the behavior of individual travelers which is analyzed and modeled (although households, organizations or other entities could also be modeled). Such models include the mathematical and logical abstractions of choice behaviors implemented in algorithms and computer software. Among the travel behaviors that are commonly modeled are route choices, mode choices (i.e. the decision to travel by car, public transport, cycling, etc.) and travel time choices (i.e. departure time), and their combinations. The behavioral assumptions applied in the analysis and modeling of travel choices can be traced back to economic theory. Discrete choice analysis are commonly applied in the analysis of travel choices and are largely based on the paradigms of random utility theory (1,2,3).

In addition and sometimes as an alternative to the traditional models of travel behavior, AI methods and techniques have been applied to model and analyze the behavior of travelers. The use of soft computing methodologies is of particular interest to transport researchers and practitioners due to their ability to handle quantitative and qualitative measures, and to efficiently solve problems which involve complexity, imprecision and uncertainty – many times applying methods that have some similarities to cognitive mechanisms applied by individuals in the process of choice making and problem solving. Moreover, the characteristics and performances of transport systems, and many of the perceived attributes of the travel alternatives in an individual's choice set, cannot always be simply defined or described on the basis of crisp and quantitative evaluation of their main effects. Much of the traveler's decisions and behaviors take place under imprecision, uncertainty and partial truth. Some objectives, criteria and constraints involved in travel choices are often difficult to be measured by crisp values, and are thus often neglected by transport modelers. Moreover, issues of travel behavior are complex and inexact, and the traditional models cannot deal effectively with travelers' ambiguities, uncertainties and vagueness. Some of these modeling challenges can be addressed by AI methods, as illustrated in the next sections.

AI PARADIGMS, COGNITIVE PSYCHOLOGY, AND TRAVEL BEHAVIOR

As Van Zuylen mentioned before in his introductory section to this Circular, AI systems and research can be classified into two categories (4). "Strong" AI research is intended to produce machines with an intelligence that matches or exceeds that of human beings. AI, in its weak form, is less ambitious: it concerns itself more with the degree to which machines can demonstrate mechanisms that underlie human behavior, but do not necessarily have consciousness, personal identity, emotions, or mind. Both forms of AI sit alongside cognitive psychology (and other behavioral sciences) at the core of an interdisciplinary approach to understanding and modeling intelligent behavior.

The main modeling tools used for the analysis modeling and prediction of travel choices stem from neoclassical economics in which individuals are assumed to make choices which are rational, consistent, perfectly informed and which maximize their economic utility by trading off between costs and benefits (5). However, research in behavioral sciences, especially cognitive psychology, indicates that individuals' choices in a wide range of contexts deviate from the predictions of the simpler forms of economic theory. Some of these deviations are systematic, consistent, robust and largely predictable. Evidence on systematic deviations from rational models have emerged from studies on financial behavior, consumer behavior, health behavior (e.g., (6,7,8,9,10)) and more recently –travel behavior (e.g. (11, 12,13,14)). This is somewhat in conflict with the traditional model of travel choice, in which travel is seen as a "derived demand", rationalized by its economic context, and travelers are expected to act as rational human beings, and exhibit consistency and transitivity in their choices.

It is clear that both AI and cognitive psychology should not be seen as two separate approaches relevant to the study of travel behavior; combining one with the other could promote both approaches to their full potential. Much of the recent work in cognitive psychology and behavioral economics focuses on the cognitive biases and the cognitive bounded rationality of decision makers; a novel approach in the study of travel behavior would be to incorporate systematic deviations of travel choice from the rational models of utility maximization into models and simulations of travel behavior; rather than aiming to develop algorithms that are based on a normative model of decision making, to 'truly' imitate the choices and behaviors of 'real' humans it would be necessary to model the biases, flaws and limitations in their processes of judging, inferencing, learning, and problem-solving, as exhibited in their travel behavior. For example, the incorporation of a cognitive psychology notions related to human perception of uncertainty into a fuzzy-based model of travel choice is illustrated in (15). To fully address the more ambitious strong AI paradigm, future research could explore the incorporation of affective factors that play a role travel choice decisions through a range of emotional states. However, current AI research and applications into the field of travel behavior is typically associated with the weak paradigm of AI.

FUZZY SETS THEORY

Uncertainty and variability of the supply and demand sides of the transport system, travel choice models mainly measure the uncertainty of the system, but not always attempt to capture the uncertainty in the mind of the traveler, and its effect on travel choices. In order to make practical use of travel-choice models in stochastic networks a link is required between objectively measurable uncertainty of the transport system and travelers' perception of that uncertainty. We can identify three key reasons why fuzzy sets theory might be relevant to applications in travel behavior. First, imprecision and vagueness are inherent to the traveler's cognitive model of behavior and choice. Second, in the transport environment, the information obtained by the traveler in the formulation of preferences, decision variables, constraints and parameters is vague or not precisely measurable. Third, imprecision and vagueness as a result of perception errors, cognitive biases and subjective opinion may further dampen the quality and quantity of available information. Hence, fuzzy sets can be used to bridge modeling gaps of normative and descriptive decision models in travel behavior research(and bring us a step closer to the "strong" paradigm of AI).

The fuzziness of perception reflects humans' limited cognitive abilities and finite ability of sensory organ to resolve detail, store and process information. Fuzzy sets theory, as a paradigm to deals with difficulties that are related to the concepts that have vague boundaries, have been fruitfully applied to a range transportation problems (16). Because travel choice cannot be separated from human perception and decision processes, it makes a good domain for fuzzy theory applications.

Since the early 90's fuzzy sets were applied in the field of travel behaviors, much of these applications have been in the modeling of the route-choice decision-making process (17,18,19,20,21), which is an essential part of any traffic assignment model.

In the existing literature there are two main approaches to construct fuzzy utility functions. The first approach is based on fuzzy graphs and allows describing human preferences over the alternatives using fuzzy production ("if-then") rules. The second approach implies construction of fuzzy-set valued functions, in particular fuzzy number-valued functions. Accordingly, fuzzy models of travel choice can be roughly separated into two types (21); models of the first type mostly derive from the initial work of Lotan et al. (19,20) and are based on fuzzy rules and on the classical tools of fuzzy control. They handle rules such as:

**"If travel time on route A is *very short*,
and travel time on route B is *intermediate*,
then the driver will *certainly* choose route A"**

Such an inference mechanism is typically applied in situations were the premises or the consequents can be described in fuzzy rather than real terms (i.e., by fuzzy variables associated with membership functions). In such a fuzzy rule-based system, the confidence with which the data match the premise is calculated; if this premise confidence is at least equal to a specified threshold value, the rule is said to be fireable, i.e. activated. When a rule is fired, the consequent actions are carried out to extract the traveler decision. The confidence with which these actions are taken depends on both the premise confidence and the confidence placed in the rule itself; this net confidence is the fuzzy AND (or minimum) of the premise and the rule confidences, and is called the posterior confidence. The premise confidence and rule-firing threshold determine whether an instance of a rule is fireable; a rule's instance is fireable if the premise confidence equals or exceeds the threshold. The posterior confidence is the confidence with which the consequent is executed, and is normally the confidence value stored with any data made or modified by the rule. For practical reasons, many models require to have the fuzzy outcome reduced into a single and crisp value representation; a deffuzification process may be therefore applied on the fuzzy consequent (22).

The second type of a fuzzy model of travel choice is based on the evaluation of possibility theory or with comparison tools that can be demonstrated to be equivalent (see, for example, (21)).

The first studies of fuzzy-based choice modeling illustrated the possibilities of fuzzy logic in solving problems using hypothetical (and sometimes rather simplistic) numerical examples. Observed behavior (or 'revealed preferences) obtained at laboratory experiments and field studies have been successfully applied to calibrate and validate fuzzy-based choice models.

Some studies suggested extending Wardrop's principle of user equilibrium (23) to accommodate principles of fuzzy sets in the formulization of the transport system's uncertainties, as perceived by the traveler; travelers' perception of generalized travel time can be modeled using a fuzzy number (24); thus, based on the perceived generalized travel times of the different route alternatives, travelers are expected to choose a route which optimizes their fuzzy travel time. An alternative approach to solve the fuzzy user equilibrium or to apply a fuzzy-based approach in the assignment is described in Wang and Liao (25). Yet the relevance of such a modeling approach to the modeling of travel behavior is a matter of empirical evidence and validation studies.

Among their applications to the study of travel behavior, fuzzy sets were also applied in the modeling of mode-choice behavior (26,27,28), daily activity schedules (29) and parking behavior (30).

NEURAL NETWORKS

Neural networks have been widely applied to a wide range of transport problems that defy traditional modeling approaches (31). Some argue that the Neural Network approach was based on the assumption that there is a similarity between the process of traveler decision-making and the problem solving approach on neural computing. In principle, however, the neural network approach is less representative of real traveler decision-making than a fuzzy rule-based model. The operation of a fuzzy rule-based model enables adjustment of rules to improve the overall performance of the model. The performance of a neural networks model can be adjusted only by re-training using alternative data (e.g., (32)). An ANFIS (Adaptive Neuro Fuzzy Inference System) approach, where a fuzzy inference system can be represented with a neural network structure (33), may be considered as a methodology that combines both approaches of soft computing to travel behavior modeling. An early example of a hybrid model is described in (34), where route-choice decision-making is modeled by a fuzzy rulebase, and a neural network approach is used for calibrating the parameters of the fuzzy model. The use of neural networks for trip generation, trip distribution and modal split models was demonstrated in a range of works

(35,36,37,38,39,40,41). Cantarella and de Luca developed a novel modeling approach and demonstrated how to apply neural networks in the analysis of mode choice (42). Their approach combines the use of multilayer feedforward networks (MLFFNs) with elements of random utility models. The proposed approach was applied to two case studies. The MLFFNs model was calibrated against revealed preferences and its performance was compared with random utility models. The results showed that the MLFFNs may outperform random utility models when the values of mode shares are similar. However, the application of MLFFNs, although being effective in the prediction of travel choices, provides very little insight on travel behavior. Compared with the traditional econometric approaches, its contribution to the understanding of the variables contributing to mode choices is rather limited, as it cannot provide clear interpretation of parameters (42).

Celikiglu observed that in most of the applications of neural networks to the modeling of travel behavior, the feed-forward back propagation neural network (FFBPNN) models or hybrid models of FFBPNNs were proposed (43). He argued that the FFBPNN algorithm has drawbacks which can lead the model to develop in an inaccurate direction, and proposed two alternative approaches for travel mode choice analysis: radial basis function neural network (RBFNN) and generalized regression neural network (GRNN).

The results reported in other studies highlight the potential of neural networks in the analysis of travel (mode) choices (42,43). Following the recent development of alternative models of travel choice, such as fuzzy sets or neural network models, there is a growing need for a systematic approach to validate and compare choice models within a general protocol. De Luca and Cantarella argued in favor of such a systematic approach, as the commonly used indicators (such as rho-square statistics) are relevant only for utility-based models and provide only little insights into model effectiveness (44). They introduced benchmarking indicators to validate and compare choice models, among them the model efficiency (computational speed and memory requirements).

For additional discussion on the advantages and limitations of Neural Networks in modeling travel behavior, see the article by Reinke featured in this circular.

GENETIC ALGORITHMS

Genetic algorithms have been applied to route-choice modeling (45,46,47). In order to examine the dynamic nature of a driver-network system through microsimulation tools, Nakayama et al. developed a theoretical model of drivers' cognition, learning, and route choice, assuming limitations in drivers' cognitive capabilities (46). In their work, a production system, which is a compilation of if-then rules, was formulated to represent alternative strategies in route choice. In the proposed system, drivers learn from experience and apply inductive reasoning. Such framework is adopted in the above study because it has its basis in cognitive psychology and is also computationally tractable. The decision rules applied in the driver's route choice process and their inferiority values are revised and updated by the application of genetic algorithms, through reproduction, crossover and mutation.

Another interesting application of genetic algorithms to travel behavior is illustrated in Pribyl and Goulias (48). The proposed approach is based on the belief that people and households with similar socio-demographic characteristics have similar travel patterns (49,50). Applying a method based on k-medoid clustering, groups of households with similar activity patterns are identified and clustered. An improvement in searching for clusters was incorporated by using genetic algorithms (48).

MULTI-AGENT SIMULATIONS

Microscopic models of travel behavior can be largely described as multi-agent simulations. Agents, representing individual travelers, households or other decision-making entities, are maintained as artificial individual entities with individual attributes and individual states, and make individual decisions based on these attributes and states. Two agents, when submitted to the same situation, can therefore make fundamentally different decisions (51). For a review of agent-based approaches to model a range of transport problems, travel behavior among them, see (52).

Such a modeling framework might be therefore considered as relatively realistic in describing the heterogeneity and the complexity in large-scale real-life settings. However it can be generally argued that the common approach in the application of multi-agent models in travel behavior is that it is not the agents that evaluate alternatives, make choices and learn, but the overall system. In that respect, most applications in this area fail to address the strong AI paradigm, and it can be argued that many multi-agent simulations should not be considered as truly AI techniques. However there is a potential in using advanced computational techniques in multi agent simulations; in a state-of-art review of computational methods, Nagel and Marchal consider parallel computing as a mature technology that can be used to speed up individual modules of such simulations (although practical applications are somewhat rare) (51). Distributed artificial intelligence, software agents and peer-to-peer systems are among the emerging computational methods that have recently attracted attention by the research community.

The modeling and analysis of travel behavior are typically disaggregated, meaning that the models represent the choice behavior of an individual entity. However, individuals are influenced by ‘significant others’, people in their social networks, and people who have geographical and social proximity. The interactions within and between travelers and social groups, and some complex behaviors such as social norms, social imitation and social learning, are not commonly formulated in travel behavior models. Although there is a growing interest in the study of social interactions in relation to travel behavior, there is not much experience with incorporating social interactions into travel behavior models. The framework of multi-agent models, which focuses on studying the patterns of social interaction among a population of agents, has been applied in the study of travel behavior (53) and in the modeling of the diffusion of transport technologies (54). Sunitiyoso et al. used laboratory experiments to reveal the learning process of travelers when making repeated travel decisions; experimental settings, such as interaction between participants and flow of information, were controlled (55). This data was used as an input to a simulation experiment utilizing an agent-based model, simulating larger group sizes, longer time periods and complex situational settings that can not explored be in the laboratory environment. It can be generally argued that agent-based models and simulations that are based primarily on normative assumptions on travel behavior might not correspond closely to travelers’ real-world contextual settings (55). Observed behaviors of ‘real’ travelers could inform the modeling and simulation of artificial entities that represent such travelers. Such an approach can also help in ensuring the relevance validity of the results in representing a wider population, and can be used to investigate the potential effects of a transport measure prior to its implementation in practice.

CONCLUSIONS

Over the last two decades there has been a growing interest in applying AI to the study of travel behavior, leading to some successful applications and implementations. This paper reviewed a range of theories and techniques, such as fuzzy sets theory, artificial neural networks, genetic algorithms and agent-based models. Although it is by no mean a complete review of AI applications in the field of travel behavior, we hope that this paper has contributed to a better understanding of the potential use of AI methodologies in this field and provide the reader with a starting point when investigating the literature dealing with such applications.

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